-:PROJECT DOCUMENTATION:-

1. INTRODUCTION:

1.1 Overview:

Demand plays a crucial role in the management of every business. It helps an organization to reduce risks involved in business activities and make important business decisions such as stock maintenance, investments, franchising, etc.

1.2 Purpose:

Demand forecasting helps reduce such risks and make efficient financial decisions that will have a positive impact on profit margins, cash flow, allocation of resources, opportunities for expansion, inventory accounting, operating costs, staffing, and overall spend.

2. LITERATURE SURVEY:

2.1 Existing problem

A food delivery service has to deal with a lot of perishable raw materials which makes it all, the most important factor for such a company is to accurately forecast daily and weekly demand. Too much inventory in the warehouse means more risk of wastage, and not enough could lead to out-of-stocks - and push customers to seek solutions from your competitors. The replenishment of majority of raw materials is done on weekly basis and since the raw material is perishable, the procurement planning is of utmost importance. For this, the company has to maintain an improved warehouse management system is required with the ability to predict the demand of goods for the next few weeks or in the near future.

2.2 Proposed Solution

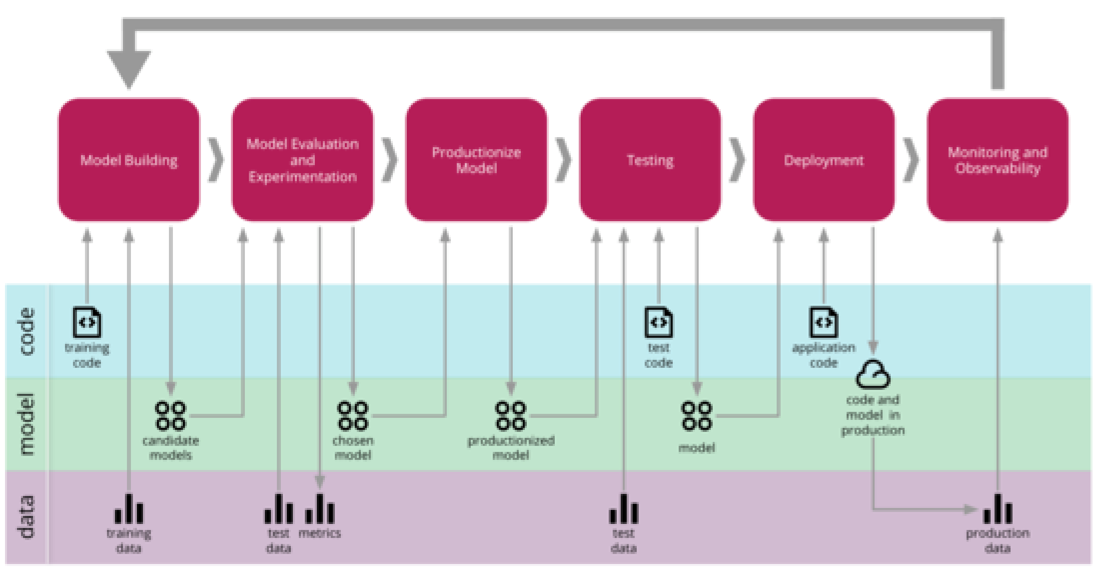
A prediction analysis model trained over a required period of time and validated over recent statistical information can possibly be able to forecast the necessary demand of the goods that are dealt with, in an accurate manner, thereby giving an idea about the quantitative maintenance of the stock in the warehouse to meet the future needs which could comply and fit as per the recent market demand considering different possible scenarios including emergency crisis like the present COVID-19 situation.

Using this as inspiration, we use attention based LSTM networks for accurate and precise prediction of demand in all the diverse type of situation and hence come up with this innovative solution.

Furthermore, such a thing could be both hosted and managed by web and app services through IBM cloud to provide the necessary details to the clients in a well perceivable manner.

3. THEORETICAL ANALYSIS:

a. Block diagram:



b. SOFTWARE DESIGNING:

The model is a Long Short Term Memory (LSTM) based model, the model is based on such a network because LSTM blocks are known to be one of the most accurate predictors when it comes to time-series data, hence this becomes the obvious choice for our solution of demand forecasting of this perishable goods.

This model is then aided with Dual-stage Attention layers inspired from the paper "A Dual-Stage Attention-Based Recurrent Neural Network for Time Series Prediction", this paper and attention was chosen because for accurate prediction of the demand forecasting a diverse variety of features were chosen to range from holidays, region-wise store data to the economy affecting oil prices of an oil-dependent economy (other features could have been chosen, but our prediction was on an oil dependent economy based country), now from this wide diversity of features it is fairly easy to get lost in inaccurate prediction unless the dependency of the result is not studied and applied while training the model, hence applying these attention layers comes in handy to overcome this problem very efficiently.

After the LSTM were made CNN-LSTM modules to extract the features in a much better way, hence enhancing the prediction. And finally an additional linear layer was added to model in order to scale up the predicted to the actual data.

After this model was trained on a time series sales data of 5 types of perishable goods of 4years, and after training this model was able to give very accurate prediction demand for these 5 perishable good across 54 different stores and regions efficiently for more than 10 weeks.

Deployment procedure-

After training the model the, the trained weights are saved in a '.pth' file which is thereafter used for prediction using local host.

The UI accepts three inputs:

01- Forecasted Day

02- Store ID

03-Product

Thereafter the inputs are passed onto the local server where the trained .pth file is loaded which accepts the value and processes it and gives a responses back to home page ans the predicted order is shown

4. EXPERIMENTAL INVESTIGATIONS:

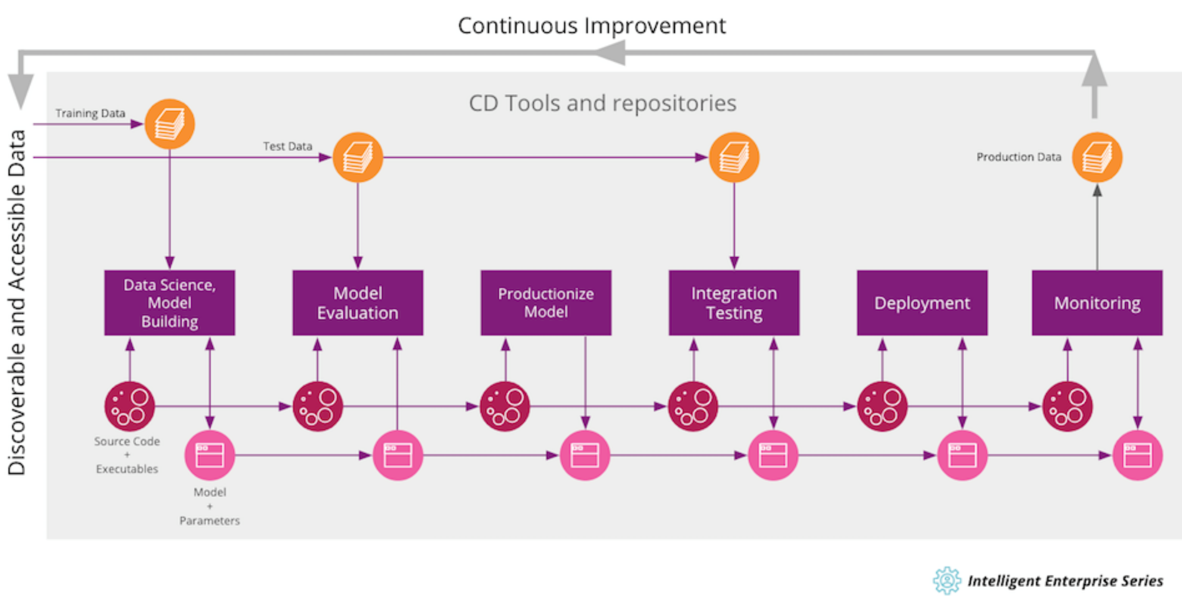
While designing our solution for this warehouse management problem, we found out the result depends on a whole variety of factors to be determined accurately.

1. This result dependant on factors like whether the day was holiday or not/
2. The specific regions where the store is present or the perishable good is sold
3. The amount of total transaction across all good this store witnessed on a particular day
4. The broad class that the perishable item belongs to
5. The price of oil (gasoline and other fossil fuel) on that particular day

These were some of the many features that we found the prediction depended on, now the type of features would remain generally the same for demand forecasting of perishable goods, but for different places and regions some extra features need to be collected for better result, the dependency on the oil prices is relevant in our dataset only because we are talking about an oil dependant economy (i.e Ecuador is an oil-dependent country and its economic health is highly vulnerable to shocks in oil prices.)

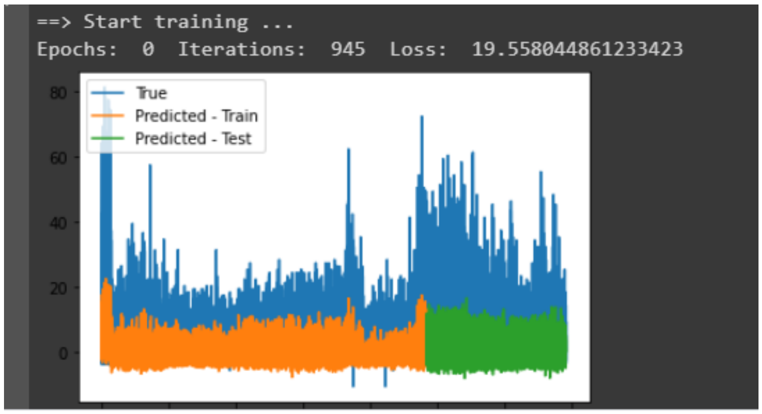
For India in place of these other factors like average rainfall (owing to the fact that it is a farming dependent economy) or other factor s depending on the locality of the region and additional factors like the number of vegetarians, number of non-vegetarian people in a population, or average income of the population and such factors could be useful for more precise region-specific prediction.

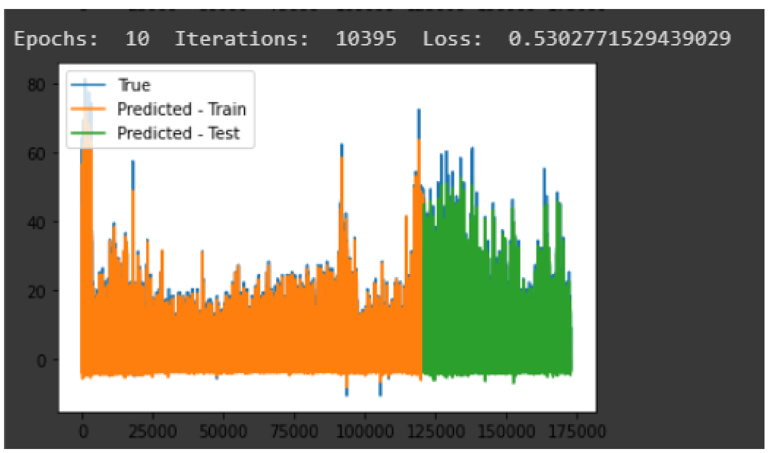
5. FLOWCHART:

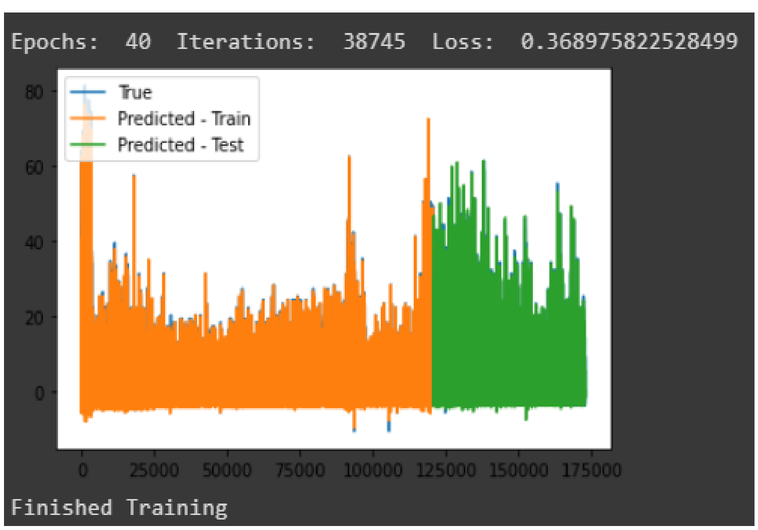


6. RESULT:

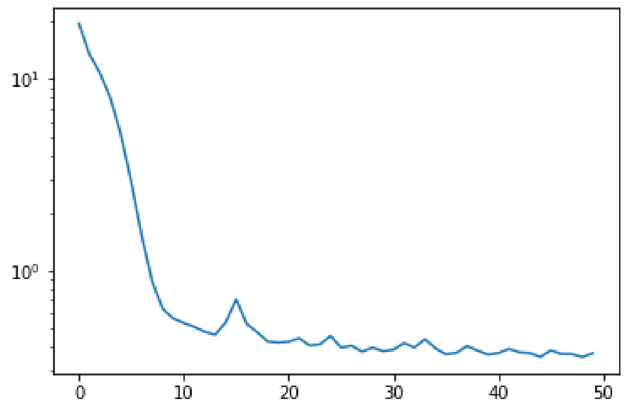
Our model is trained on the dataset consisting of 5 different perishable goods for 4 years across 54 different stores. Here are some of the visualised result.



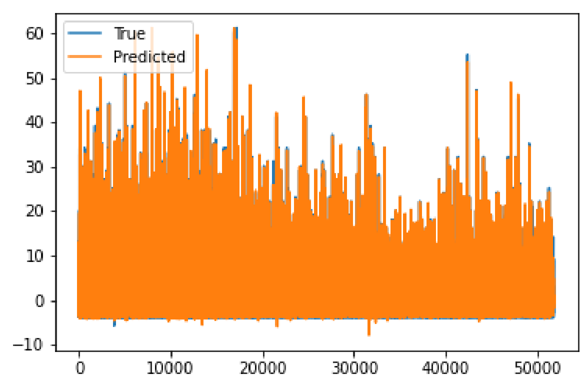




Loss optimisation during training period:



Following is the final ground truth vs prediction output on test data which has no training data included in it:



7. ADVANTAGES & DISADVANTAGES:

Advantages-

1. Our solution will give an accurate prediction for a long period of time even more than 10 weeks of prediction can be easily obtained with our solution.
2. It can be used to predict demand for not just a single but rather a whole variety of products,

3. It can also be used to predict the products for different perishable good at different locations, so it is also a region invariant solution hence more versatile

Disadvantages-

1. The solution at the present state is not very efficient for predicting the demand accurately for new goods which don’t have any historical sales data.
2. The demand forecasting solution of ours is not very accurate in predicting hourly demand, it can accurate results only if data is predicted for a day or two.

8. APPLICATIONS:

This solution whose machine learning architecture is based on robust CNN–LSTM backbone supported by dual-stage attention layers is designed to provide an efficient solution, hence it can be used for a variety of demand forecasting, not only restricted to perishable goods but also other goods including essentials like medicine and oil.

This method so built can also be used for efficient region-wise demand prediction for services like internet, and presently needed ventilators, essential drugs and many among others, hence this should be used for better inventory management of the essentials goods and services region wise which would prove to be invaluable in an extreme situation like the present COVID 19 situation.

9. CONCLUSION:

The prediction model has been effectively designed and trained with sufficient amount of data and information required, thus it gives constructive results which have been cross checked with the validation set. So, it could successfully predict the demand and trend of different food items and also during the process continuous update in the existing database occurs which improves its accuracy further.

10. FUTURE SCOPE:

In the future, this solution could be improved to give a prediction on new products and services based on various input factors like advertisement circulation, hype study from social media, blogs, and other internet sources.

This can be also used to generate short span predictions like hourly prediction which would prove to be essential in the fields like water supply system, energy demand and hence regulating energy generation from sources like a windmill, solar panels etc.

This solution currently based on demand forecasting of perishable good would also prove to be useful in various other fields if provided and trained with a dataset based on that field, hence this could be used as a versatile solution for all the different kind of field where prediction can be made with historical data.

11. BIBLIOGRAPHY:

1. https://arxiv.org/pdf/1704.02971.pdf
2. https://www.kaggle.com/c/favorita-grocery-sales-forecasting/data
3. https://discuss.pytorch.org/t/why-3d-input-tensors-in-lstm/4455
4. http://chandlerzuo.github.io/blog/2017/11/darnn
5. https://github.com/YitongCU/Duel-staged-Attention-for-NYC-Weather-prediction

6. https://arxiv.org/pdf/1902.10877.pdf
7. https://discuss.pytorch.org/t/seq2seq-model-with-attention-for-time-series-forecasting/80463
8. https://discuss.pytorch.org/t/pytorch-sequence-to-sequence-modelling-via-encoder-decoder-for-time-series/23683

12. APPENDIX:

```
# -*- coding: utf-8 -*-
"""PREDICTION MODEL FOR WAREHOUSE MANAGEMENT SYSTEM.ipynb

Automatically generated by Colaboratory.

Original file is located at
    https://colab.research.google.com/drive/1xlR40kfcLbBQZSnr_keEnap_N5-6VKp6

# DA RNN

Google Drive Mount
"""

from google.colab import drive
drive.mount('/content/drive')

cd drive/My\ Drive

cd 'Colab Notebooks'

ls

"""## Hyper-parameters settings"""

#THE PATH FOR DATSET IS DATAROOT
dataroot = '/content/drive/My Drive/Datasets/demand fore4casting/data_more_features_final.csv'
#dataroot = '/content/data_test1 (1).csv'
batchsize = 128
nhidden_encoder = 128
```

```
nhidden_decoder = 128
ntimestep = 7
lr = 0.001
epochs = 50

"""## Model Architecture"""

import matplotlib.pyplot as plt

from torch.autograd import Variable

import torch
import numpy as np
from torch import nn
from torch import optim
import torch.nn.functional as F
from  sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
class Encoder(nn.Module):
    """encoder in DA_RNN."""

    def __init__(self, T,
                 input_size,
                 encoder_num_hidden,
                 parallel=False):
        """Initialize an encoder in DA_RNN."""
        super(Encoder, self).__init__()
        self.encoder_num_hidden = encoder_num_hidden
        self.input_size = input_size
        self.parallel = parallel
        self.T = T

        # Fig 1. Temporal Attention Mechanism: Encoder is LSTM
        self.encoder_lstm = nn.LSTM(
            input_size=self.input_size,
            hidden_size=self.encoder_num_hidden,
            num_layers = 1
        )
        self.cnn=nn.Conv1d(self.input_size,7,1)
        #self.cnn=nn.Conv1d(self.input_size,7,1)
        #self.cnn2=nn.Conv1d(104,7,1)
        #self.cnn3=nn.Conv1d(105,7,1)


```

```python
        # Construct Input Attention Mechanism via deterministic attention model
        # Eq. 8: W_e[h_{t-1}; s_{t-1}] + U_e * x^k
        self.encoder_attn = nn.Linear(
            in_features=2 * self.encoder_num_hidden + self.T - 1,
            out_features=1
        )

    def forward(self, X):
        """forward.

        Args:
            X: input data

        """
        X_tilde = Variable(X.data.new(
            X.size(0), self.T - 1, self.input_size).zero_())
        X_encoded = Variable(X.data.new(
            X.size(0), self.T - 1, self.encoder_num_hidden).zero_())

        # Eq. 8, parameters not in nn.Linear but to be learnt
        # v_e = torch.nn.Parameter(data=torch.empty(
        #     self.input_size, self.T).uniform_(0, 1), requires_grad=True)
        # U_e = torch.nn.Parameter(data=torch.empty(
        #     self.T, self.T).uniform_(0, 1), requires_grad=True)

        # h_n, s_n: initial states with dimention hidden_size
        h_n = self._init_states(X)
        s_n = self._init_states(X)

        for t in range(self.T - 1):
            # batch_size * input_size * (2 * hidden_size + T - 1)
            x = torch.cat((h_n.repeat(self.input_size, 1, 1).permute(1, 0, 2),
                           s_n.repeat(self.input_size, 1, 1).permute(1, 0, 2),
                           X.permute(0, 2, 1)), dim=2)

            x = self.encoder_attn(
                x.view(-1, self.encoder_num_hidden * 2 + self.T - 1))

            # get weights by softmax
            alpha = F.softmax(x.view(-1, self.input_size))
```

```

            # get new input for LSTM
            x_tilde = torch.mul(alpha, X[:, t, :])
            #print( x_tilde.shape)
            # Fix the warning about non-contiguous memory
            # https://discuss.pytorch.org/t/dataparallel-issue-with-flatten-parameter/8282
            self.encoder_lstm.flatten_parameters()

            # encoder LSTM
            '''
            if(x_tilde.shape[0]==105):
              x_tilde1=x_tilde
              x_tilde1.unsqueeze_(-1)
              x_tilde1=x_tilde1.expand(105,7,1)
              x_tilde1=self.cnn( x_tilde1)
              x_tilde1.unsqueeze_(-1)
              x_tilde=x_tilde1.view(105, 7)

            elif(x_tilde.shape[0]==104):
              x_tilde1=x_tilde
              x_tilde1.unsqueeze_(-1)
              x_tilde1=x_tilde1.expand(104,7,1)
              x_tilde1=self.cnn( x_tilde1)
              x_tilde1.unsqueeze_(-1)
              x_tilde=x_tilde1.view(104, 7)
            '''
            #else:
            #self.cnn=nn.Conv1d(x_tilde.shape[1],7,1)
            x_tilde1=x_tilde
            x_tilde1.unsqueeze_(-1)
            x_tilde1=x_tilde1.expand(x_tilde.shape[0],7,1)
            x_tilde1=self.cnn( x_tilde1)
            x_tilde1.unsqueeze_(-1)
            x_tilde=x_tilde1.view(x_tilde.shape[0], 7)

            _, final_state = self.encoder_lstm(x_tilde.unsqueeze(0), (h_n, s_n))
            h_n = final_state[0]
            s_n = final_state[1]

            X_tilde[:, t, :] = x_tilde
            X_encoded[:, t, :] = h_n
```

```python

        return X_tilde, X_encoded

    def _init_states(self, X):
        """Initialize all 0 hidden states and cell states for encoder.

        Args:
            X

        Returns:
            initial_hidden_states
        """
        # https://pytorch.org/docs/master/nn.html?#lstm
        return Variable(X.data.new(1, X.size(0), self.encoder_num_hidden).zero_())


class Decoder(nn.Module):
    """decoder in DA_RNN."""

    def __init__(self, T, decoder_num_hidden, encoder_num_hidden):
        """Initialize a decoder in DA_RNN."""
        super(Decoder, self).__init__()
        self.decoder_num_hidden = decoder_num_hidden
        self.encoder_num_hidden = encoder_num_hidden
        self.T = T

        self.attn_layer = nn.Sequential(
            nn.Linear(2 * decoder_num_hidden + encoder_num_hidden, encoder_num_hidden),
            nn.Tanh(),
            nn.Linear(encoder_num_hidden, 1)
        )
        self.lstm_layer = nn.LSTM(
            input_size=1,
            hidden_size=decoder_num_hidden
        )
        self.fc = nn.Linear(encoder_num_hidden + 1, 1)
        self.fc_final = nn.Linear(decoder_num_hidden + encoder_num_hidden, 1)

        self.fc.weight.data.normal_()
```

```python

    def forward(self, X_encoded, y_prev):
        """forward."""
        d_n = self._init_states(X_encoded)
        c_n = self._init_states(X_encoded)

        for t in range(self.T - 1):

            x = torch.cat((d_n.repeat(self.T - 1, 1, 1).permute(1, 0, 2),
                           c_n.repeat(self.T - 1, 1, 1).permute(1, 0, 2),
                           X_encoded), dim=2)

            beta = F.softmax(self.attn_layer(
                x.view(-1, 2 * self.decoder_num_hidden + self.encoder_num_hidden)).view(-1, self.T - 1))

            # Eqn. 14: compute context vector
            # batch_size * encoder_hidden_size
            context = torch.bmm(beta.unsqueeze(1), X_encoded)[:, 0, :]
            if t < self.T - 1:
                # Eqn. 15
                # batch_size * 1
                y_tilde = self.fc(
                    torch.cat((context, y_prev[:, t].unsqueeze(1)), dim=1))

                # Eqn. 16: LSTM
                self.lstm_layer.flatten_parameters()
                _, final_states = self.lstm_layer(
                    y_tilde.unsqueeze(0), (d_n, c_n))

                d_n = final_states[0]  # 1 * batch_size * decoder_num_hidden
                c_n = final_states[1]  # 1 * batch_size * decoder_num_hidden

        # Eqn. 22: final output
        y_pred = self.fc_final(torch.cat((d_n[0], context), dim=1))

        return y_pred

    def _init_states(self, X):
        """Initialize all 0 hidden states and cell states for encoder.

```

```
        Args:
            X
        Returns:
            initial_hidden_states

        """
        # hidden state and cell state [num_layers*num_directions, batch_size, hidden_size]
        # https://pytorch.org/docs/master/nn.html?#lstm
        return Variable(X.data.new(1, X.size(0), self.decoder_num_hidden).zero_())


class DA_rnn(nn.Module):
    """da_rnn."""

    def __init__(self, X, y, T,
                 encoder_num_hidden,
                 decoder_num_hidden,
                 batch_size,
                 learning_rate,
                 epochs,
                 parallel=False):
        """da_rnn initialization."""
        super(DA_rnn, self).__init__()
        self.linear_reg=LinearRegression()
        self.encoder_num_hidden = encoder_num_hidden
        self.linear=nn.Linear(128,128)
        self.decoder_num_hidden = decoder_num_hidden
        self.learning_rate = learning_rate
        self.batch_size = batch_size
        self.parallel = parallel
        self.shuffle = False
        self.epochs = epochs
        self.T = T
        self.X = X
        self.y = y

        #self.device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
        self.device = torch.device('cpu')
        print("==> Use accelerator: ", self.device)

        self.Encoder = Encoder(input_size=X.shape[1],
```

```
                               encoder_num_hidden=encoder_num_hidden,
                               T=T).to(self.device)
        self.Decoder = Decoder(encoder_num_hidden=encoder_num_hidden,
                               decoder_num_hidden=decoder_num_hidden,
                               T=T).to(self.device)

        # Loss function
        self.criterion = nn.MSELoss()

        if self.parallel:
            self.encoder = nn.DataParallel(self.encoder)
            self.decoder = nn.DataParallel(self.decoder)

        self.encoder_optimizer = optim.Adam(params=filter(lambda p: p.requires_grad,
                                            self.Encoder.parameters()),
                                            lr=self.learning_rate)
        self.decoder_optimizer = optim.Adam(params=filter(lambda p: p.requires_grad,
                                            self.Decoder.parameters()),
                                            lr=self.learning_rate)



        self.Linear_optimizer = optim.Adam(params=filter(lambda p: p.requires_grad,
                                           self.linear.parameters()),
                                           lr=self.learning_rate)




        # Training set
        self.train_timesteps = int(self.X.shape[0] * 0.7)
        self.y = self.y - np.mean(self.y[:self.train_timesteps])
        self.input_size = self.X.shape[1]

    def train(self):
        """training process."""
        iter_per_epoch = int(np.ceil(self.train_timesteps * 1. / self.batch_size))
```

```
        self.iter_losses = np.zeros(self.epochs * iter_per_epoch)
        self.epoch_losses = np.zeros(self.epochs)

        n_iter = 0

        for epoch in range(self.epochs):
            if self.shuffle:
                ref_idx = np.random.permutation(self.train_timesteps - self.T)
            else:
                ref_idx = np.array(range(self.train_timesteps - self.T))

            idx = 0

            while (idx < self.train_timesteps):
                # get the indices of X_train
                indices = ref_idx[idx:(idx + self.batch_size)]
                # x = np.zeros((self.T - 1, len(indices), self.input_size))
                x = np.zeros((len(indices), self.T - 1, self.input_size))
                y_prev = np.zeros((len(indices), self.T - 1))
                y_gt = self.y[indices + self.T]

                # format x into 3D tensor
                for bs in range(len(indices)):
                    x[bs, :, :] = self.X[indices[bs]:(indices[bs] + self.T - 1), :]
                    y_prev[bs, :] = self.y[indices[bs]: (indices[bs] + self.T - 1)]

                loss = self.train_forward(x, y_prev, y_gt)
                self.iter_losses[int(epoch * iter_per_epoch + idx / self.batch_size)] = loss

                idx += self.batch_size
                n_iter += 1

                if n_iter % 10000 == 0 and n_iter != 0:
                    for param_group in self.encoder_optimizer.param_groups:
                        param_group['lr'] = param_group['lr'] * 0.9
                    for param_group in self.decoder_optimizer.param_groups:
                        param_group['lr'] = param_group['lr'] * 0.9
```

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                self.epoch_losses[epoch] = np.mean(self.iter_losses[range(
                    epoch * iter_per_epoch, (epoch + 1) * iter_per_epoch)])





            if epoch % 10 == 0:
                print("Epochs: ", epoch, " Iterations: ", n_iter,
                      " Loss: ", self.epoch_losses[epoch])

            if epoch % 10 == 0:
                y_train_pred = self.test(on_train=True)
                y_test_pred = self.test(on_train=False)
                y_pred = np.concatenate((y_train_pred, y_test_pred))

                plt.ioff()
                plt.figure()
                plt.plot(range(1, 1 + len(self.y)), self.y, label="True")
                plt.plot(range(self.T, len(y_train_pred) + self.T),
                         y_train_pred, label='Predicted - Train')
                plt.plot(range(self.T + len(y_train_pred), len(self.y) + 1),
                         y_test_pred, label='Predicted - Test')
                plt.legend(loc='upper left')
                plt.show()

            # # Save files in last iterations
            # if epoch == self.epochs - 1:
            #     np.savetxt('../loss.txt', np.array(self.epoch_losses), delimiter=',')
            #     np.savetxt('../y_pred.txt',
            #                np.array(self.y_pred), delimiter=',')
            #     np.savetxt('../y_true.txt',
            #                np.array(self.y_true), delimiter=',')

    def train_forward(self, X, y_prev, y_gt):
        """
        Forward pass.

        Args:
```

```
            X:
            y_prev:
            y_gt: Ground truth label

        """
        # zero gradients
        self.encoder_optimizer.zero_grad()
        self.decoder_optimizer.zero_grad()



        self.Linear_optimizer.zero_grad()


        input_weighted, input_encoded = self.Encoder(
Variable(torch.from_numpy(X).type(torch.FloatTensor).to(self.device)))
        y_pred = self.Decoder(input_encoded, Variable(
torch.from_numpy(y_prev).type(torch.FloatTensor).to(self.device)))

        if (y_pred.shape[0]==128):
          y_pred=self.linear(y_pred.view(-1,y_pred.shape[0]*1))
          y_pred=y_pred.T
        #print(y_pred.shape)


        y_true = Variable(torch.from_numpy(
            y_gt).type(torch.FloatTensor).to(self.device))

        y_true = y_true.view(-1, 1)
        y_pred1=y_pred
        #y_pred =y_pred.detach().numpy()
        #self.linear_reg.fit(y_true,y_pred)
        #y_pred=self.linear_reg.predict(y_true)


        #y_pred=torch.abs(y_pred)
        loss = self.criterion(y_pred1, y_true)
        loss.backward()

        self.encoder_optimizer.step()
        self.decoder_optimizer.step()

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```
        self.Linear_optimizer.step()


        return loss.item()


    def test(self, on_train=False):
        """test."""

        if on_train:
            y_pred = np.zeros(self.train_timesteps - self.T + 1)
        else:
            y_pred = np.zeros(self.X.shape[0] - self.train_timesteps)

        i = 0
        while i < len(y_pred):
            batch_idx = np.array(range(len(y_pred)))[i: (i + self.batch_size)]
            X = np.zeros((len(batch_idx), self.T - 1, self.X.shape[1]))
            y_history = np.zeros((len(batch_idx), self.T - 1))

            for j in range(len(batch_idx)):
                if on_train:
                    X[j, :, :] = self.X[range(
                        batch_idx[j], batch_idx[j] + self.T - 1), :]
                    y_history[j, :] = self.y[range(
                        batch_idx[j], batch_idx[j] + self.T - 1)]
                else:
                    X[j, :, :] = self.X[range(
                        batch_idx[j] + self.train_timesteps - self.T, batch_idx[j] + self.train_timesteps - 1), :]
                    y_history[j, :] = self.y[range(
                        batch_idx[j] + self.train_timesteps - self.T, batch_idx[j] + self.train_timesteps - 1)]

            y_history = Variable(torch.from_numpy(
                y_history).type(torch.FloatTensor).to(self.device))
            _, input_encoded = self.Encoder(
                Variable(torch.from_numpy(X).type(torch.FloatTensor).to(self.device)))
            y_pred[i:(i + self.batch_size)] = self.Decoder(input_encoded,
                y_history).cpu().data.numpy()[:, 0]
```

```

            y_pred_copy=y_pred

            if (y_pred[i:(i + self.batch_size)].shape[0]==128):
                y_pred1 =y_pred[i:(i + self.batch_size)]
                y_pred1=torch.from_numpy(y_pred1)
                y_pred1=y_pred1.float()

                y_pred1=self.linear(y_pred1.view(-1,y_pred[i:(i + self.batch_size)].shape[0]*1))

                #y_pred[:,i:(i + self.batch_size)]=self.linear(y_pred1.view(-1,y_pred1.shape[0]*1))
                y_pred1=y_pred1.T
                y_pred1=y_pred1.detach().numpy()
                y_pred[i:(i + self.batch_size)]= y_pred1.ravel()

            '''

        if (y_pred.shape[0]==128):
          y_pred=self.linear(y_pred.view(-1,y_pred.shape[0]*1))
          y_pred=y_pred.T

            y_pred= y_pred.reshape(-1, 1)

            #y_pred[i:(i + self.batch_size)]=self.linear_reg.predict(y_pred[i:(i + self.batch_size)])


            y_pred=y_pred.reshape(y_pred_copy.shape)
            '''

            i += self.batch_size

        return y_pred
    def predict(self,X1,days):
        X1=X1
        y_pred = np.zeros(X1.shape[0])
        i = 0
        while i < len(y_pred):
            batch_idx = np.array(range(len(y_pred)))[i: (i + self.batch_size)]
            X = np.zeros((len(batch_idx), self.T - 1, X1.shape[1]))
```

```
            y_history = np.zeros((len(batch_idx), self.T - 1))

            for j in range(len(batch_idx)):


                    X[j, :, :] = X1[range(
                        batch_idx[j]  - self.T, batch_idx[j]  - 1), :]
                    y_history[j, :] = self.y[range(
                        batch_idx[j]  - self.T, batch_idx[j]  - 1)]

            y_history = Variable(torch.from_numpy(
                y_history).type(torch.FloatTensor).to(self.device))
            _, input_encoded = self.Encoder(
Variable(torch.from_numpy(X).type(torch.FloatTensor).to(self.device)))
            y_pred[i:(i + self.batch_size)] = self.Decoder(input_encoded,
y_history).cpu().data.numpy()[:, 0]

            y_pred_copy=y_pred

            if (y_pred[i:(i + self.batch_size)].shape[0]==128):
                y_pred1 =y_pred[i:(i + self.batch_size)]
                y_pred1=torch.from_numpy(y_pred1)
                y_pred1=y_pred1.float()

                y_pred1=self.linear(y_pred1.view(-1,y_pred[i:(i +
self.batch_size)].shape[0]*1))
                y_pred1=y_pred1.T
                y_pred1=y_pred1.detach().numpy()
                y_pred[i:(i + self.batch_size)]= y_pred1.ravel()
            i += self.batch_size
        plt.ioff()
        plt.figure()
        plt.plot(range(1, 1 + len(y_pred[:days])),y_pred[:days],
label="Predicted")
        plt.legend(loc='upper left')
        plt.show()
        return y_pred

"""## Util Function"""

import numpy as np
import pandas as pd
```

```python
from sklearn import preprocessing
from sklearn.preprocessing import MinMaxScaler

def read_data(input_path, debug=True):
    """Read nasdaq stocks data.

    Args:
        input_path (str): directory to nasdaq dataset.

    Returns:
        X (np.ndarray): features.
        y (np.ndarray): ground truth.

    """
    df = pd.read_csv(input_path, nrows=365 if debug else None)
    #df = pd.read_csv(input_path)
    df=df.drop(['id','date','Unnamed: 0.1'], axis = 1)

    # X = df.iloc[:, 0:-1].values
    X = df.loc[:, [x for x in df.columns.tolist() if x != 'unit_sales']].to_numpy()

    # y = df.iloc[:, -1].values
    y = np.array(df.unit_sales)
    y=y.reshape(-1, 1)
    #use the below function if you want to normalize
    '''

    scaler = MinMaxScaler(feature_range=(0, 1))
    scaler = scaler.fit(y)
    '''
   # y= scaler.transform(y)
    #y = preprocessing.scale(y)
    print(y)
    y=y.reshape(-1)
    return X, y

"""## Main"""

# Read dataset
import warnings
warnings.filterwarnings("ignore")
print("==> Load dataset ...")
X, y = read_data(dataroot, debug=False)
```

```python

# Initialize model
print("==> Initialize DA-RNN model ...")
model = DA_rnn(
    X,
    y,
    ntimestep,
    nhidden_encoder,
    nhidden_decoder,
    batchsize,
    lr,
    epochs
)

# Train
print("==> Start training ...")
#model.to(device)
model.train()

# Prediction
y_pred = model.test()

fig1 = plt.figure()
plt.semilogy(range(len(model.iter_losses)), model.iter_losses)
plt.savefig("1.png")
plt.close(fig1)

fig2 = plt.figure()
plt.semilogy(range(len(model.epoch_losses)), model.epoch_losses)
plt.savefig("2.png")
plt.close(fig2)

fig3 = plt.figure()
plt.plot(model.y[model.train_timesteps:], label="True")
plt.plot(y_pred, label='Predicted')

plt.legend(loc='upper left')
plt.savefig("3.png")
plt.close(fig3)
print('Finished Training')

"""SAVING THE TRAINEDD MODEL"""

torch.save(model, '/content/drive/My Drive/Datasets/demand
```

```
fore4casting/finished.pth')

"""# LOADING THE  TRAINED MODEL"""

model = torch.load('/content/drive/My Drive/Datasets/demand
fore4casting/finished.pth')

"""FUNTION TO TAKE CUSTOM INPUT AND FEED IT TO MODEL FOR PREDICTION"""

import random
def backend():

  days=input("input number of days" )
  store_nbr=input("enter the store nmbr ranging from 1 to 54: ")
  item_nbr=input("enter the item nmbr any one of the following
(108696),(164088),(804098),(1695936),(2032088)")
  days = int(days)
  store_nbr = int(store_nbr)
  item_nbr = int(item_nbr)



  dcoilwtico=[]
  itemnbr=[]
  storenbr=[]
  onpromotion=[]
  transactions=[]
  type1=[]
  y=days%128
  days1=days+y
  for x in range(days1):
    itemnbr.append(item_nbr)
    storenbr.append(store_nbr)
    dcoilwtico.append(random.randint(26,110))
    onpromotion.append( random.randint(0,1))
    transactions.append(random.randint(6,8359))
    type1.append(random.randint(0,1))
  unnamed=list(range(0,days1))
dict1={'unnamed':unnamed,'store_nbr':storenbr,'item_nbr':itemnbr,'onpromotion':onpromotion,'dcoilwtico':dcoilwtico,'transactions':transactions,
        'type':type1}
  data=pd.DataFrame(dict1)
  return data ,days
```

```python
import numpy as np
import pandas as pd
from sklearn import preprocessing
from sklearn.preprocessing import MinMaxScaler

def read_data1(input, ):
    """Read nasdaq stocks data.

    Args:
        input_path (str): directory to nasdaq dataset.

    Returns:
        X (np.ndarray): features.
        y (np.ndarray): ground truth.

    """
    df = input
    #df = pd.read_csv(input_path)


    # X = df.iloc[:, 0:-1].values
    X = df.loc[:, [x for x in df.columns.tolist() if x !=
'unit_sales']].to_numpy()

    # y = df.iloc[:, -1].values
    '''
    y = np.array(df.unit_sales)
    y=y.reshape(-1, 1)

    scaler = MinMaxScaler(feature_range=(0, 1))
    scaler = scaler.fit(y)

   # y= scaler.transform(y)
    #y = preprocessing.scale(y)
    print(y)
    y=y.reshape(-1)
    '''
    return X

"""# SAMPLE OUTPUT FROM A CUSTOM INPUT"""

x,d= backend()

pred=model.predict(read_data1(x),d)
```

```
pred = np.absolute(pred)
#print(pred[:d][d-1])
```